



**HAL**  
open science

# Firm–bank “odd couples” and trade credit: Evidence from Italian small- and medium-sized enterprises

Jérémie Bertrand, Pierluigi Murro

► **To cite this version:**

Jérémie Bertrand, Pierluigi Murro. Firm–bank “odd couples” and trade credit: Evidence from Italian small- and medium-sized enterprises. *Economic Modelling*, 2022, 111, pp.105829. 10.1016/j.econmod.2022.105829 . hal-03703975

**HAL Id: hal-03703975**

**<https://hal.science/hal-03703975v1>**

Submitted on 22 Jul 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

## **Firm–bank “odd couples” and trade credit: Evidence from Italian small- and medium-sized enterprises<sup>1</sup>**

**Jérémie BERTRAND<sup>2</sup>**

IESEG School of Management & LEM CNRS

**Pierluigi MURRO<sup>3</sup>**

LUISS University

### **Abstract**

One of the most crucial obstacles for small- and medium-sized enterprises is access to credit primarily because of their high opacity. The existing literature underlines that relationship banks specialize in analyzing opaque firms, thereby allowing them better access to credit; however, what can opaque firms do if they cannot find a relationship bank? By using an Italian database, with more than 900 firms, we reveal that when opaque firms deal with transactional banks (the “odd couples”), they use a greater portion of trade credit. This result is robust to alternative measures of trade credit and lending technologies. We further analyze the mechanisms driving the association between odd couples and trade credit use. Regression results suggest that the positive association is particularly significant for firms with more market power, not “captured” by their primary bank, and located in areas with high levels of social capital.

*JEL: G21, L14, L22*

*Keywords: Banks, Lending Technologies, Small Business, Trade Credit*

---

<sup>1</sup> We wish to thank the editor, the associate-editor, the copy-editor, the anonymous referees, and seminar and conference participants for helpful comments and conversations. All remaining errors are ours.

<sup>2</sup> IESEG School of Management, Univ. Lille, CNRS, UMR 9221 - LEM - Lille Economie Management, 3 rue de la Digue - 59000 Lille (France). Tel.: +33 320 54 58 92. Email: [j.bertrand@ieseg.fr](mailto:j.bertrand@ieseg.fr).

<sup>3</sup> Department of Business and Management, LUISS University. Viale Romania, 32, 00197 Rome – Italy. Email: [pmurro@luiss.it](mailto:pmurro@luiss.it). Corresponding Author

## 1. Introduction

Trade credit is a crucial financing source for small- and medium-sized enterprises (SMEs) because payables represent a substantial fraction of corporate assets (Giannetti et al., 2011; Murro and Peruzzi, 2021). Existing literature identifies some determinants of the use of trade credit (Giannetti, 2003; Demirgüç-Kunt and Maksimovic, 2002); however, no consensus is observed regarding the relationship between trade credit and bank financing. On the one hand, the conventional substitution hypothesis predicts that for the receiving firm, trade credit and bank loans represent substitute sources of external financing; firms struggling to borrow from banks depend on credit extended by their suppliers (Mateut et al., 2006; Garcia-Appendini and Montoriol-Garriga, 2013; Casey and O'Toole, 2014). On the other hand, the complementarity hypothesis suggests that using trade credit is an indicator of firms' quality for financial intermediaries, thereby reducing their adverse selection problems and credit rationing (Burkart and Ellingsen, 2004; McMillan and Woodruff, 1999; Atanasova, 2012). According to this perspective, sellers have private information on buyers, which is similar to or even superior to the information available to banks (Mian and Smith, 1992; Biais and Gollier, 1997; Wilner, 2000), which they use to make better lending decisions.

The empirical literature validates that long relationships between buyers and sellers improve trade credit availability, thereby highlighting that suppliers behave similarly to relationship-oriented lenders using soft information to make lending decisions (Wilner, 2000; Cuñat, 2007; Uchida et al., 2013).<sup>4</sup> Subsequently, these findings raise a question: Can trade credit be a funding substitute for opaque firms that cannot obtain bank relationship credit? If so, under what conditions?

According to Berger et al. (2005) and Stein (2002), more opaque firms, primarily providing soft information, must borrow from smaller, relationship-oriented banks that can better evaluate such information. By contrast, large banks may enjoy competitive advantages from financing more transparent firms because they can exploit the economies of scale associated with processing and transmitting hard information. However, the possibility of an imperfect firm-type/bank-type match arises, i.e., a situation wherein the information characteristics of the firms

---

<sup>4</sup> Banks generally use two lending approaches concerning SMEs: transaction-based and relationship lending (Berger and Udell, 2002; Stein, 2002). Transaction-based lending implies that the decisions are based on quantitative (hard) information readily available at loan origination (e.g., borrowers' balance sheets, collateral guarantees). With relationship lending, the bank bases its decisions on qualitative (soft) information about the firm obtained through personal interaction, which is difficult to codify (Berger and Udell, 2006).

and its bank's lending technology are not aligned (Ferri and Murro, 2015).<sup>5</sup> In a perfect banking market, the consequences of a mismatch would be immaterial because they could be immediately overcome. However, Ferri and Murro (2015) suggest that transaction and information costs could force the firm in a "wrong" relationship, thereby increasing the bank's probability of being credit rationed. Until now, no papers have examined the effects of a bank–firm mismatch on trade credit.

This paper investigates whether opaque firms use more trade credit when experiencing firm–bank mismatches. We further study how the firms' characteristics, bank nature, and socioeconomic environment affect the trade credit-mismatch association. To identify these effects, we utilize data from the tenth wave of the Survey of Italian Manufacturing Firms (SIMF) for 2004–2006 conducted by UniCredit Bank in 2007. This data set offers three primary advantages for our analysis. First, it comprises accounting information indicating the importance of trade credit to firms' funding. Second, for the first time, this tenth wave included a set of questions regarding bank–firm relationships and firms' perceptions of their banks, thereby enabling us to construct two continuous indicators of lending technologies; the first indicator captures the degree of relationship lending, whereas the second one captures the degree of transactional lending. These indicators correspond more closely with reality than the discrete measures available in the previous studies (i.e., whether a bank is involved in transactional or relationship lending at a particular moment) (Berger and Black, 2011). Third, the data set is based on Italian firms, which represents an appropriate testing ground for isolating the association between trade and bank credit. In Italy, bank credit is the most critical source of financing for SMEs (Minetti, 2011); however, trade credit is a crucial alternative source; on average, it accounts for 42% of the total assets, which is the highest percentage in Europe (Giannetti, 2003).

Our results show that opaque firms considering their banks as transactional solicit more trade credit, thereby empirically supporting our argument that these mismatched firms use trade credit to substitute for relationship lending. However, this effect is observed only among older

---

<sup>5</sup> Few papers have investigated the causes and consequences of mismatches to the best of our knowledge. For example, changes in the bank organization might lead them to switch from relationship to transactional approaches, which creates a firm–bank mismatch where previously there had been a match (Ferri and Murro, 2015). Bonaccorsi Di Patti and Gobbi (2007) find that bank mergers affect these structural organizations and change credit availability. As Hale (2012) shows, banks drastically reduce their relationships with clients during financial crisis periods and favor transactional lending technology. A mismatch also might result from firms' ability to observe bank organizations accurately; if firms misperceive their financial partners ex-ante, such as by judging them to be relationship banks, a mismatch arises when they are actually transactional (Ferri and Murro, 2015).

and larger SMEs possibly because of their greater capacity for negotiation compared with smaller or younger firms. Moreover, the opaque firms use less trade credit when deals with relationship banks because trade credit is more expensive<sup>6</sup> than bank credit (if correctly evaluated). Finally, our results vary with the nature of the banks (national or local) and the structures of the firms' banking pools because we outline in detail in the results section.

Section 2 provides a survey of trade credit research and presents our theoretical predictions; Section 3 presents our data and methodology, and Section 4 reports the results. Section 5 concludes.

## **2. Related literature and theoretical predictions**

### **2.1. Trade credit theories**

Theories that explain trade credit use can be classified into two primary groups: use based on real operations and on financial advantages. In the first group, for example, [Ferris \(1981\)](#) offers transaction cost minimization theory, according to which trade credit can reduce the cost of delivering multiple goods by assigning unique monthly or quarterly payments. Trade credit further offers firms with time to evaluate product quality ([Smith, 1987](#)) and a means to manage their inventories and cash flow more easily in accordance with their needs. [Brennan et al. \(1988\)](#) show that creditworthy customers pay promptly to receive any available discounts, whereas risky customers find the price of trade credit attractive relative to other options.

The second group of theories ([Mian and Smith, 1992](#); [Cuñat, 2007](#); [Palacín-Sánchez et al., 2019](#)) indicates some distinct advantages offered by trade creditors. In their model, [Fabbri and Menichini \(2010\)](#) report that suppliers acquire private information more easily than banks, and thus, these trade creditors have less asymmetric information and can offer credit to opaque firms when the banks cannot. Thus, for constrained firms, trade credit substitutes for bank credit. Empirical evidence validates this substitution effect; for example, [Petersen and Rajan \(1994\)](#) show that firms with sufficient bank credit depend less on trade credit. [Garcia-Appendini and Montoriol-Garriga \(2013\)](#) analyzed the accounts payable of U.S. public firms during the 2007–2008 financial crisis; they found results consistent with a demand effect, wherein credit flowed from liquid suppliers to their most constrained clients (see also [Hyun, 2021](#), in Korea). [Minetti et al. \(2019\)](#) further find that increased exposure to bank credit rationing enable firms to be more likely to participate in supply chains for overcoming liquidity shortages. According to

---

<sup>6</sup> A “2/10 net 30” agreement (i.e., take a 2% discount if the firm pays in 10 days, otherwise pay in 30 days) is equivalent to an implicit interest rate of 43.9% for firms that do not take the discount ([Ng et al., 1999](#)).

Molina and Preve (2012), firms in financial distress use a significantly larger amount of trade credit to substitute for alternative financing sources. Other researchers report that substitution becomes more critical when firms increase in age and size (Casey and O’Toole, 2014; Klapper et al., 2012; Cosci et al., 2020).

Some theoretical arguments further suggest complementarity between trade and bank credit. Biais and Golier (1997) develop a model wherein positive information in the availability of trade credit induces banks to lend; Burkart and Ellingsen (2004) further suggest that the availability of trade credit increases the amount the banks are willing to lend. In this perspective, bank and trade credit complement firms whose aggregate debt capacity constrains investments. Moreover, Cuñat (2007) provides a complementary explanation for trade credit usage: suppliers have an advantage in lending to customers because they can halt the provision of inputs. From an empirical perspective, McMillan and Woodruff (1999) find no relationship between offering trade credit and receiving bank loans, whereas firms appear to receive more trade credit if they obtain a bank loan. Agostino and Trivieri (2014) estimate that firms using trade credit have a higher likelihood of obtaining bank credit; these chances may increase with more acute information asymmetries. Finally, Andrieu et al. (2018) use survey data on European SMEs during 2009–2014 to identify a complementary effect between trade credit and bank financing application success.

## 2.2. Bank–firm mismatch and trade credit

Banking literature emphasizes the influence of lending technologies on credit availability for firms. Berger and Udell (2006, p. 2946) define a lending technology as “a unique combination of primary information source, screening and underwriting policies/procedures, loan contract structure and monitoring strategies/mechanisms.” As presented in footnote 1, two general lending technologies exist: relationship and transactional technologies (Berger and Udell, 2006; Bartoli et al., 2013). The primary difference is the bank’s information source used to make lending decisions and monitor loans. Relationship lending is based on soft, qualitative information obtained through personal interaction, which is generally difficult to codify or transfer (Rajan, 1992). By contrast, transactional lending is based primarily on hard, quantitative information, which may be obtained from balance sheets or collateral guarantees provided by the firms (Berger and Udell, 2006; Bartoli et al., 2013). Therefore, transaction lending technology must be more appropriate for transparent firms; however, relationship lending technology is likely more suitable for opaque firms, which by definition tend to be more affected by information asymmetries (Berger et al., 2005; Stein, 2002). Despite this consensus

regarding a preferable combination, firm–bank mismatches are possible because “In a perfect capital market, events that create a mismatch would be immaterial, since it could be immediately unwound. However, transaction and information costs could make it difficult to change the banking partner, and the firm might end up stuck (for a while) with the ‘wrong’ bank, thereby possibly suffering more credit rationing than would have resulted from a perfect match” (Ferri and Murro, 2015, p. 232).

The potential detrimental impacts of a bank–firm mismatch are notable. Suppose opaque firms match with transactional banks, their probability of being credit rationed increases. To the best of our knowledge, no existing research has explicitly considered the effects of a bank–firm mismatch on trade credit. Murro and Peruzzi (2021) suggest that credit use increases when the duration of this relationship is longer. However, Agostino and Trivieri (2014) assert that trade credit has stronger positive effects on bank financing when banks cannot accumulate soft information.

### 2.3. Hypotheses

Existing theories citing the financial advantages of trade credit indicate that strong buyer–seller relationships enable trade creditors to acquire information regarding buyers’ financial quality (Biais and Gollier, 1997; Burkart and Ellingsen, 2004). For example, Cuñat (2007) shows that long-term buyer–supplier relationships support the development of shared, informal technology that benefits both parties and cannot be provided by other lenders. Long-term relationships further allow firms to renegotiate debt more easily with sellers (Wilner, 2000). Uchida et al. (2013) show that a longer buyer–supplier relationship increases the amount of credit provided by sellers, although this beneficial effect depends on relative levels of bargaining power. If a buyer depends substantially on its primary supplier, the supplier does not provide more credit with longer relationships. Moreover, according to industrial organization research (e.g., Johnson et al., 2002), trade credit duration affects buyers’ payment decisions; a longer relationship yields credit payments, whereas shorter relationships favor cash payments. Finally, Minetti et al. (2019) find that the liquidity benefits of supply chains are particularly strong when firms establish long-term relationships with their trading partners.

This combined evidence reveals that trade creditors can function in the same roles as banks using relationship lending technology to accumulate and use soft information. For firms, information production and management yield the same advantages as relationship lending technology: better access to credit and better credit conditions even for firms in a downturn.



Therefore, in cases of mismatch, opaque firms may be more prone to use trade credit as a funding alternative. To avoid being misevaluated, these firms may borrow more from their trade creditors, which can better evaluate their soft information. In this case, we should observe a higher level of trade credit for opaque firms in cases of mismatch:

***H1: Opaque firms encountering banks that use transactional lending technology to obtain a higher proportion of trade credit than opaque firms facing banks using relationship lending technology.***

However, trade credit is more expensive than bank credit, and when firms are liquidity-unrestricted and have access to relationship lending technology, they may favor cheaper bank credit over expensive trade credit (Biais and Gollier, 1997; Burkart and Ellingsen, 2004). That is, opaque firms have no reason to substitute bank credit with trade credit if they are appropriately evaluated; when they interact with banks managing soft information, they should have lower trade credit:

***H2: Opaque firms that encounter banks using relationship lending technology obtain a lower portion of trade credit than opaque firms facing banks using transactional lending technology.***

### **3. Methodology and data**

#### **3.1. Data sources**

The database comes from the 10<sup>th</sup> wave of the SIMF, which UniCredit conducted in 2007 covering 2004–2006 (see Table A1 for details about the variables).<sup>7</sup> It contains information on approximately 4,500 Italian manufacturing firms with more than 10 employees. This database's strength is extensive information regarding firms, including balance sheets, income statements, ownership structures, numbers and skill degrees of employees, research and development (R&D), internationalization and export, and—perhaps of the greatest interest—firm relationships with the banking system and financial management from the firms' perspective. By leveraging each firm's insights on its primary bank and its relationship with that bank, we can analyze the firm's choices according to its perceptions.<sup>8</sup> This repeated survey has proved

---

<sup>7</sup> This survey has been widely used in the empirical literature on Italian manufacturing firms, particularly on firms' financial constraints and relationship banking. Amongst others, see Alessandrini et al. (2010), Bartoli et al. (2013), and Ferri and Murro (2015). However, no one had yet used this survey to study the substitutability between trade credit and relationship bank credit.

<sup>8</sup> Although self-reported data can raise reliability concerns, we do not regard them as a problem for our study. First, firms have no incentive to lie about their performance to establish themselves as appealing borrowers because



crucial input for prior research as well. For example, [Presbitero and Zazzaro \(2011\)](#) use the data to analyze the effect of market concentration on relationship lending, [Herrera and Minetti \(2007\)](#) study the impact of relationship lending on firm innovation capability, and [Minetti and Zhu \(2011\)](#) investigate the impact of credit rationing on firms' exports.

Particularly relevant for our analysis, the SIMF's 2007 wave featured a new set of questions expressly designed to investigate the relationship between the firm and its primary bank ([Ferri and Murro, 2015](#)). Unfortunately, only one-third of the surveyed firms (1,541 firms) answered this survey section. Table A2 presents descriptive statistics for the complete and selected sample. As suggested by *t* tests on the equality of the means, we cannot rule out self-selection. Firms that answered these questions are slightly older and larger than the sample mean; however, they have similar characteristics, such as leverage, profitability, or distribution across sectors. On average, our sample's firms are 30.2 years old and have 138 employees; 60% of the firms have fewer than 50 employees (less than 4% have more than 500 employees); 71% are based in North Italy. Only 1% are listed on the Stock Exchange, and 24.4% have balance sheets certified by external auditors. The majority of firms are corporations (96.8%), and more than one-quarter belong to a group or consortium. On average, firms have relationships with an average of 5.6 banks and an average relationship length of approximately 15 years with their primary bank, which is local in approximately 60% of the cases. For our analyses, we further complement these insights with data from other sources, including data from the Bank of Italy on the presence of banks in local markets; we also incorporate data provided from the Italian National Statistics Office on the provinces' added value and populations.

### 3.2. Methodology

To test our hypotheses, we use the following model:

$$y_i = \alpha + \beta * soft_i + \gamma * LT_i + \delta * (soft_i * LT_i) + \theta * control + \varepsilon_i, (1)$$

where  $y_i$  indicates the importance of trade credit in firm funding;  $soft_i$  is a measure of the opaqueness of the firm (i.e., need for soft information).  $LT_i$  is the lending technology used to finance the firm,  $soft_i * LT_i$  is their interaction term,  $control$  is a vector of control variables, and  $\varepsilon_i$  is a vector of heteroskedastic robust standard errors<sup>9</sup>.

---

Italian law regarding personal data (675/1996) forbids their use for any objectives other than compiling statistical tables. Second, the firms' responses underwent multiple checks by highly qualified personnel.

<sup>9</sup> For each model, we test the validity of the results by looking at specification tests and residual analysis. Results are available upon request.

### 3.3. Variables

#### 3.3.1. Trade credit

We seek to explain the use of trade credit according to the type of information provided by the firm and lending technology adopted by the bank. Trade credit use can be divided into two terms: quantity and duration. As a measure of trade credit's quantity, we use one proxy, namely, TC/TL, which is the ratio of the amount of trade credit to the total loan for the firm at the end of December 2006. As a robustness check, we apply three alternative measures of trade credit as follows: (1) TC/TA, which is the ratio of the amount of trade credit to the total assets of the firm at the end of December 2006; (2) TC/STL or the ratio of the amount of trade credit to total outstanding short-term loans at the end of December 2006; (3) DPO (days payable outstanding), a measure of the duration of trade credit or how long it takes for the firm to pay invoices from its suppliers is equal to following:

$$DPO = \frac{\text{average trade payable}_{2006}}{\text{cost of goods sold}_{2006}} * 360.$$

The higher the ratio, the more important it is for the firm to be liquid. We use ordinary least square models in all cases because all our dependent variables are continuous.

#### 3.3.2. Lending technologies

Regarding lending technology, a methodology proposed by [Bartoli et al. \(2013\)](#) is applied to develop two indicators: one for transactional lending technology (LT\_TRANS) and one for relationship lending technology (LT\_REL). To capture the lending technology that the firm respondents believe their banks use, they answer to the following survey question: "In your view, what criteria does your bank follow in granting loans to you?" The respondents provide weights from 1 (very important) to 4 (nil) concerning 15 items. Table 1 displays the items, each item's answer distribution, and how each item is classified in constructing the indicators.

As per the results, the respondents believe that accounting is the most crucial criterion. Approximately 20% of the sample selected 1 (very important) for criteria 1–4, whereas approximately 10% select other items. Therefore, firm respondents believe banks use accounting information more than other information.

**Table 1: Items used to construct lending technology indicators**

This table displays the 15 items used to answer the question, "In your view, what criteria does your bank follow in granting loans to you?" and the distribution of the answers to each item, from 1 (very important) to 4 (nil), as well as how each item is classified to construct the lending technology indicators, as relationship (R) or transactional (T).

---

Items	1	2	3	4	T/R
1. Ability of the firm to repay its debt (e.g., years needed to repay debt)	20.39%	44.73%	8.55%	25.33%	T
2. Financial solidity of the firm (capital/asset ratio)	20.29%	47.37%	7.11%	25.23%	T
3. Firm's profitability (current profits/sales ratio)	18.23%	44.80%	10.09%	26.88%	T
4. Firm's growth (growth of sales)	18.74%	41.92%	13.59%	25.75%	T
5. Ability of the firm to post real estate (not personal) collateral	9.89%	41.40%	18.64%	30.07%	T
6. Ability of the firm to post tangible non-real estate collateral	8.24%	42.43%	18.54%	30.79%	T
7. Support by a guarantee association (e.g., loan, export, R&D)	13.18%	31.31%	15.14%	40.37%	
8. Personal guarantees by the firm's manager or owner	11.33%	46.14%	9.27%	33.26%	T
9. Managerial ability on the part of those running the firm's business	12.46%	49.02%	11.12%	27.39%	R
10. Strength of the firm in its market (number of customers, commercial network)	10.71%	44.49%	15.65%	29.15%	R
11. Intrinsic strength of the firm (e.g., ability to innovate)	14.93%	44.59%	13.18%	27.29%	R
12. Firm's external evaluation or its evaluation by third parties	10.61%	44.39%	16.27%	28.73%	
13. Length of the lending relationship with the firm	11.33%	48.20%	13.29%	27.19%	R
14. Loans granted when the bank is the firm's main bank	11.33%	50.98%	9.17%	28.53%	R
15. Fiduciary bond between the firm and the credit officer at your bank	11.49%	49.54M	11.12%	25.85%	R

Regarding transactional lending technology, [Berger and Udell \(2006\)](#) consider six possible transaction-based lending technologies: financial statements, small business credit scoring, asset-based lending, factoring, fixed-asset lending, and leasing. Unfortunately, the survey provides information for only three of these technologies: financial statements (items 1–4), real estate (item 5), and other fixed assets (items 6 and 8). We construct an aggregate variable (LT\_TRANS) equal to the average of seven dummy variables; these variables take a value of 1 if the firm assigns a value of 1 to the aforementioned lending items. The higher the variable, the more the firm regards its bank as transactional.

[Berger and Udell \(2006\)](#) explain that relationship lending technology is primarily based on soft information and developed through contacts over time. It represents qualitative information regarding the firm, such as manager reliability or its intrinsic strength ([Stein, 2002](#)). We focus on all items that can correspond to one of these characteristics: items 9, 10, 11, 13, 14, and 15. The aggregate variable (LT\_REL) is equal to the average of six dummy variables, which takes a value of 1 if the firm respondent answers 1 in response to the lending items.<sup>10</sup>

In a further robustness check, we use two new lending technology indicators, namely, *MAINTRANS* and *MAINREL*, to capture the primary lending technology used by the bank.

<sup>10</sup> As a robustness check, we compute alternative indexes of lending technologies by using (the average of) the dummies, which takes a value of 1 if the firm assigns a value of 1 or 2 to the corresponding factors in Table 1. The results, available on request, are qualitatively similar.

*MAINTRANS* is a dummy variable equal to 1 if *LT\_TRANS* is larger than the 75% percentile of the distribution and *LT\_REL* is lower than 75% and 0 otherwise. *MAINREL* is a dummy variable equal to 1 if *LT\_REL* is larger than the 75% percentile of the distribution and *LT\_TRANS* is lower than 75% and is 0 otherwise. Using these variables, we can identify the primary lending technology used by the bank and reduce the potential confounding effect of a simultaneous use of both technologies (Bartoli et al., 2013).

### 3.3.3. Firm's opaqueness (need for soft information)

Using a methodology similar to Uchida et al. (2012) and Bartoli et al. (2013), an opaqueness indicator is constructed by capturing the firm's demand for soft information during the credit application. Starting with the following question: "Which characteristics are key in selecting your main bank?" We measure the firms' needs for soft information. Table 2 shows the firm respondents assign weights ranging from 1 (very important) to 4 (nil) for 14 items.

**Table 2: Items used to construct the soft indicator**

This table displays the 14 items used to answer the question, "Which characteristics are key in selecting your main bank?" and the distribution of the answer to each item, from 1 (very important) to 4 (nil).

Items	1	2	3	4
1. The bank knows you and your business.	25.64%	45.21%	4.12%	25.03%
2. The bank knows a member of your Board of Directors or the owners of the firm.	13.49%	52.63%	7.83%	26.06%
3. The bank knows your sector.	14.83%	51.80%	8.65%	24.72%
4. The bank knows your local economy.	11.74%	55.61%	7.93%	24.72%
5. The bank knows your relevant market.	9.37%	54.58%	9.99%	26.06%
6. Frequent contact with the credit officer at the bank.	14.93%	50.26%	9.99%	24.82%
7. The bank takes quick decisions.	18.33%	44.70%	12.77%	24.20%
8. The bank offers a large variety of services.	18.23%	49.33%	8.14%	24.30%
9. The bank offers an extensive international network.	14.62%	44.90%	14.11%	26.36%
10. The bank offers efficient internet-based services.	12.67%	46.24%	14.32%	26.78%
11. The bank offers stable funding.	11.74%	47.27%	13.08%	27.91%
12. The bank offers funding and services at low cost.	13.80%	43.36%	14.52%	28.32%
13. The bank's criteria to grant credit are clear.	13.70%	46.04%	14.62%	25.64%
14. The bank is conveniently located.	16.48%	46.76%	11.23%	25.54%

The most crucial characteristic for the firm is the first item: "The bank knows you and your business" (25.64% of the sample). This finding reveals the importance of the firm's relationship with its bank. The following two most important characteristics are the seventh and eighth items (respectively, 18.33% and 18.23%), thereby showing that customers' primary preoccupations include saving time and the availability of all services in the same bank.

To construct our indicator, we select two items: the bank knows you and your business and frequent contact with the credit officer at the bank. These items both refer to banks' reliance on soft information (Ferri and Murro, 2015), and thus, they should enable to measure the firm's

ex-ante need for soft information. The *SOFT* dummy variable takes a value of 1 if the firm's respondent answers 1 for both items.<sup>11</sup> In our sample, 8.65% of the firms agreed that the bank's attitude toward soft information was a key determinant of selecting their primary bank. Table A3 displays the correlation matrix between the dependent variables, lending technologies, and soft information proxies.

### 3.4. Control variables

We include three control variables: bank controls, firm controls, and macroeconomic controls. For the bank variables, we define *NATIONAL* as a dummy variable, which is equal to 1 if the primary bank is national or foreign and 0 if it is a smaller mutual bank, larger-sized cooperative bank, savings bank, or another type of bank.

For the firm variables, we control for several characteristics: firm quality, use of leverage, and profitability (Bartoli et al., 2011). To control for the (lack of) firm opaqueness, we control for the portion of tangible assets (FA/TA) and the dummy *AUDIT*, which equals to 1 if the firm has a certified accounting statement (potential hard information emitted) and to 0 otherwise (McNamara et al., 2017). We control for the firm size by using the logarithms of the firm age and the number of employees (Cucculelli et al., 2019). To control for the firm's relationship with financial institutions, we add the logarithm of the number of institutions the firm deals with (Log Bank), the distance between the firm and its main bank (Distance), the length of their relationship (Rel. Length), and whether the bank has already rationed the firm (Credit Rationed). Furthermore, we include dummy variables indicating whether a firm is a corporation or belongs to a business group or consortium (Ferri et al., 2019). Finally, we control for the firm's geographic location by using dummy variables for each of the 103 provinces in Italy and its sector, with dummy variables for each of the six sectors represented in the database: agriculture, wholesale, construction, industrial production, service, and transport.<sup>12</sup>

Finally, the last group of control variables comprises macroeconomic variables. First, we control for the economic environment and investment opportunities by using the gross domestic product (GDP) of the province wherein the firm is located (Niskanen and Niskanen, 2006) and the loans/deposit ratio, which is a proxy for the traditional function of banks, that is, the

---

<sup>11</sup> We also compute the *SOFT* index using two alternative strategies as a robustness check. First, we consider all the firms that assign the highest importance to at least one of the two factors (1 and 6) in Table 2. Second, we include item 2 from Table 2 in the *SOFT* index. The results obtained with these alternative measures, available on request, are qualitatively similar.

<sup>12</sup> We use two-digit ATECO dummies for the firms' sectors as a robustness check. These results, available on request, are qualitatively similar.

transformation of deposits into loans (Aiello and Bonanno, 2015). The higher the ratios, the better the economy and the greater the investment opportunities. Second, we include provincial Herfindahl-Hirschman indexes (HHI) for the bank branches to control for bank competition that can affect the use of trade credit (Demirgüç-Kunt and Maksimovic, 2002; Murro, 2013). Third, we add the number of civil suits pending in each judicial district in Italy to address judicial efficiency (Herrera and Minetti, 2007); more pending civil suits imply a more inefficient legal system (Bianco et al., 2005).

## 4. Results

### 4.1. Trade credit and lending technologies

Table A4 comprises the results on the determinants of trade credit. The interaction term *SOFT* \* *LT\_TRANS* is positive and highly significant (Column 1); neither *LT\_REL* nor *LT\_TRANS* is significant. When faced with transactional banks, opaque firms (with greater needs for soft information) feature more trade credit in their loans than other firms. However, firms that rely more on hard information do not change this balance regardless of encountering relationship or transactional banks; this finding confirms H1. In cases of mismatch, wherein opaque firms encounter transactional banks, they substitute trade credit for bank credit. It further supports Uchida et al.'s (2013) hypothesis that trade creditors behave similarly to relationship lenders.

Our transactional indicator (*LT\_TRANS*) comprises three technologies: financial statements, real estate, and other fixed assets. We decompose this indicator into three subindicators, namely, *LT\_FS*, *LT\_RE*, and *LT\_OF*, to capture each technology. In Columns 2–5, we test Equation 1, thereby replacing our transactional indicator with each sub-indicator, first separately and then together, to determine whether the substitution is the same for all technologies. Firms substitute their bank loans only when they think their bank relies on their financial statements (Columns 2 and 5) and real estate (Columns 3 and 5) but not their fixed assets (Columns 4 and 5).

Regarding whether opaque firms reduce the quantity of trade credit they obtain when they match well with their bank as predicted in H2, we find only weak evidence. The interaction term *LT\_REL* \* *SOFT* is negative and significant, thereby suggesting that opaque firms in good matches have less trade credit as a proportion of their total loans. However, the interaction term coefficient is significant only in some specifications (Columns 1 and 5).

The results for the firm-specific controls reflect the evidence in prior literature; the older the firm, the greater the importance of trade credit to its funding. As indicated by Casey and

O'Toole (2014), older firms depend on trade credit more than younger firms. Consistent with expectations, trade credit further decreases with the number of banking relationships, whereas the coefficient of the length of the relationship with the primary bank is not significant.

Consistent with Demirgüç-Kunt and Maksimovic (2002), greater branch concentration in the province (HHI) is associated with the higher use of trade credit. Concerning our measure of economic investment opportunities, both *Loans/Deposits* and *GDP* are positive and significant variables. With greater investment opportunities, the use of trade credit increases. This result may seem unexpected; extant literature suggests that better investment opportunities improve bank credit availability, thereby leading to less reliance on other funding (Huyghebaert, 2006). However, Niskanen and Niskanen (2006) recognize that more investment opportunities lead to an increased need for credit than banks can provide; in these conditions, firms also turn to trade credit.

Finally, regarding legal system efficiency, the use of trade credit increases with the number of civil suits pending in the judicial district. This result is consistent with the theory that when the legal system is inefficient and does not protect banks, the use of bank credit reduces, and alternative funding increases (Demirgüç-Kunt and Maksimovic, 2002).

#### 4.2. Robustness tests

Table A5 contains the results of some robustness checks.<sup>13</sup> Columns 1–3 use an alternative measure of trade credit (*TC/TA*, *TC/STL*, and *DPO*) as dependent variables. Columns 4–7 use the two alternative indicators outlined in Section 3.3.2: *MAINTRANS* and *MAINREL*. When the technology used is transactional, opaque firms obtain a higher portion of trade credit than others regardless of whether we use *LT\_TRANS* (Columns 1–3) or *MAINTRANS* (Columns 4–7) as an indicator of transactional lending.<sup>14</sup> This consistency strongly validates the primary results for H1. When using *MAINREL*, the findings further suggest that opaque firms in a good match obtain less trade credit than others (Columns 4–7), supporting H2.

### 5. Disentangling the mechanisms

This section uses the richness of the database to understand mechanisms that associated firm–bank relationships with trade credit.

---

<sup>13</sup> To conserve space, we do not include all control variables; these results are available on request.

<sup>14</sup> We also test the impact of each sub-indicator of *LT\_TRANS* on the proxies of trade credit; the results remain the same and are available on request.



## 5.1. Firm characteristics

[Klapper et al. \(2012\)](#) and [Casey and O’Toole \(2014\)](#) show that larger and older firms use more trade credit than smaller firms when constrained by banks. Perhaps because of their size and longer relationships with suppliers, they can negotiate better trade credit conditions than smaller, younger firms. Therefore, a particularly high level of trade credit is observed for larger and older opaque firms in a mismatch. However, larger and older firms further have more audited financial statements, which may enable them to switch more easily to another creditor. [Berger and Udell \(1995\)](#) argue that age can proxy firms’ publicly available information. As a firm’s age increases, the quantity of information available increases; the firm can leverage this information to switch to a transactional banking system if relationship lending is not available. Thus, the use of trade credit should be more critical for smaller and younger firms.

Table A6 displays the results when we split the sample according to three firm characteristics: size (Columns 1 and 2), age (Columns 3 and 4), and the presence of audited statements (Columns 5 and 6). Only older, larger, and audited firms use more trade credit in a mismatch situation.<sup>15</sup> The interaction term *SOFT \* LT\_TRANS* is positive and significant only in Columns 2, 4, and 6. Moreover, the interaction term *SOFT \* LT\_REL* is significant and negative for older and larger firms. These results indicate that firms with more market power receive more trade credit from their suppliers ([Dass et al., 2015](#); [Fabbri and Klapper, 2016](#)).

## 5.2. Bank–firm relationship characteristics

[De Bodt et al. \(2015\)](#) show that mismatching may lead firms to approach a greater number of banks in an effort to be evaluated accurately. In this case, what happens if a firm already has a large pool of banks? We split the sample based on the number of banks, run Equation (1) for each subsample, and then provide the results in Table A7. Column 1 corresponds to the results for subsamples wherein firms have the pools of three banks or fewer, whereas Column 2 features firms with pools of more than three banks. The interaction term *SOFT \* LT\_TRANS* is positive and significant only if the firm has a smaller pool of banks (Column 1). Only firms in a mismatch with a few banks increase their proportion of trade credit.

Regarding the length of the relationship, because transmitting information requires time and is costly for firms, firms sharing soft information may become “informally captured” by their bank ([Sharpe, 1990](#); [Rajan, 1992](#)). Therefore, firms that have a dedicated effort to developing

---

<sup>15</sup> We split the sample using the mean value for age (30.247 years) and size (138.405 employees). As a robustness check, we use a threshold of 50 employees. The results, available on request, are qualitatively similar.

a long relationship with their bank might be less able to switch banks; they would be more inclined to switch to trade credit. The results validate this hypothesis. Splitting the sample by the length of the relationship (Table A7, Columns 3 and 4), we find substitution only by those firms that have been in a relationship with their bank for no more than two years.<sup>16</sup>

### 5.3. Bank characteristics

[Berger et al. \(2005\)](#) demonstrate that larger national banks have an advantage in managing hard information and that smaller local banks have an advantage in managing soft information because of their respective decision-making organizational structures. [Ferri and Murro \(2015\)](#) find that the impact of a mismatch on credit rationing is greater when the primary bank is a local bank. Subsequently, we expect trade credit to be more relevant in the case of a mismatch if the primary bank is a local bank. In Columns 1 and 2 of Table A8, we split the sample according to the nature of the primary bank. The findings validate the prediction; the interaction term *SOFT \* LT\_TRANS* is significant only when the primary bank is local.

In Columns 3 and 4 of Table A8, we study the role of loan officer turnover. Banks can avoid diluting soft information by delegating lending authority to the collecting agent, the loan officer ([Stein, 2002](#); [Liberti and Mian, 2009](#)). Moreover, [Hertzberg et al. \(2010\)](#) find that a rotation policy for loan officers relates to the bank's implemented lending technology. Therefore, we expect rationing that is conditional on mismatch to be less probable if the loan officers' turnover is infrequent; however, turnover frequency in the bank does not seem to affect firms in a mismatch substituting bank credit with trade credit (the interaction term *SOFT \* LT\_TRANS* is significant in Columns 3 and 4).

### 5.4. Economic and social characteristics

Finally, the economic and social environment can affect the use of trade credit in various ways (e.g., trust in banks, judicial efficiency, and economic development). We split our sample by the firm's location in Italy (North, Center, and South). These three Italian macro-regions differ significantly in their socioeconomic development ([D'Onofrio et al., 2019](#)). The North includes regions with the highest levels of GDP per capita, and the South is poorer and features lower levels of trust ([Guiso et al., 2004](#); [Murro and Peruzzi, 2019](#)). In Table A9, Columns 1–3 display the results, thereby revealing that substitution is primarily effective in Italy's North and Center

---

<sup>16</sup> As a robustness check, we split the sample using a threshold of 5 years. The results, available on request, are qualitatively similar.

but not in the South. This finding suggests that substitution is more likely when local economic development is higher.

[Guiso et al. \(2004\)](#) find that social capital also impacts financial development in different areas; high social capital encourages strengthened financial developments. To capture this effect, we use [Guiso et al.'s \(2004\)](#) measure (see Table A1) and split the sample at the mean (Columns 4 and 5 of Table A9). This assessment reveals that opaque firms use more trade credit in a case of mismatch only in areas with strong social capital, thereby confirming the relevance of socioeconomic conditions for determining access to alternative sources of credit.

## **6. Endogeneity of mismatch and trade credit**

Our estimations may be affected by endogeneity. We assume that opaque firms interacting with transactional banks increase their trade credit levels because they are more credit rationed by the bank; however, the level of trade credit may determine the relationship between the firm and its bank. Firms with a high level of trade credit may not substantially depend on bank loans to manage more transactional banks. Moreover, credit-constrained firms may be incentivized to depend more on trade credit and signal banks and to improve their access to bank credit ([Minetti et al., 2019](#)).

We manage this potential endogeneity by using an instrumental variable regression. We consider six instrumental variables because we must address endogeneity for our soft and lending technology indicators. Following [Ferri and Murro \(2015\)](#), we use an index of firm self-confidence, which is the average of the dummies constructed from characteristics 7, 8, 9, 10, 11, 12, and 14 concerning the question, “Which characteristics are key in selecting your main bank?” (Table 2). This variable captures “the importance that a firm places on the ex-ante transactional features of its main bank” ([Ferri and Murro, 2015, p. 248](#)). When this variable takes a higher value, the firm’s need for soft information is lower.

Then, as additional instruments, we use the provincial quantity of banks’ M&A activity over 2002–2006, loan officer turnover, the functional distance between hierarchical levels in the province during 2000–2005 ([Alessandrini et al., 2010](#)), and the provincial level average of the transactional and relationship lending indicators. Mergers and acquisitions tend to alter a bank’s strategy, and thus, a higher M&A activity in the province implies a greater chance of potential changes leading to a potential mismatch ([Ferri and Murro, 2015](#)). Regarding the functional distance between hierarchical levels for banks in the same province as the firm, the number of branches operating in the province, each weighted by the logarithm of 1 plus the kilometric

distance between that province's capital and the capitals of provinces where the parent banks are headquartered (Alessandrini et al., 2010). A high functional distance tends to deteriorate the bank's potential soft information use, thereby potentially altering the bank's lending technology use. The average provincial levels of the transactional and relationship proxies (*Province LT\_TRANS* and *Province LT\_REL*) further capture potential local effects on the technology used by the bank (Caprio et al., 2007). These variables exhibit a relatively high correlation with the explanatory variable and are almost uncorrelated with the amount of trade credit.

Table A10 displays our results. Concerning the three endogenous variables, more frequently loan officer turnover increases the bank's probability of using transactional lending technology and reduces relationship lending, which is consistent with Hertzberg et al. (2010). Further, the functional distance negatively affects the use of relationship lending. The self-confident index decreases soft information usage consistent with Ferri and Murro (2015).

Furthermore, the *SOFT\*LT\_TRANS* interaction indicator is positive and significant in all columns, thereby confirming our baseline results. Notably, the coefficient of the *SOFT\*LT\_REL* interaction is negative and significant in all columns, thereby suggesting that a good match between an opaque firm and a relational bank reduces trade credit use. Therefore, our results seem robust to potential endogeneity concerns.

## 7. Conclusion

The question of why firms use trade credit has remained an important puzzle in finance. Two primary explanations are predominant: real operations and financial motives. We adopt the latter perspective and consider the effect of firm–supplier relationships, as formalized by Uchida et al. (2013), who show that trade creditors can act as relationship lenders. This article further asks whether trade credit can substitute for relationship credit when firms cannot otherwise find such credit. Using an Italian database, we gather strong evidence that opaque firms faced with transactional banks obtain more trade credit as a proportion of their global debt. By contrast, opaque firms reduce the proportion of obtained trade credit when interacting with relationship banks. These results are particularly evident for larger and older firms, thereby confirming Klapper et al.'s (2012) results. These older and larger firms seemingly substitute bank credit with trade credit more easily when their banks do not correctly evaluate them. We find that this substitution depends on several parameters. The number of bank relationships the firm has and the length of its relationship with the primary bank reduce the probability of an opaque firm in a mismatched relationship with its bank using trade credit, thereby suggesting

the relevance of switching costs. Finally, the economic development and high levels of social capital increase the substitution effect.

These findings suggest some policy actions to decrease switching costs for firms without exogenously reducing the relevance of relationship lending for banks. Such policies would help smoothen the financial frictions for firms through bank or trade credit.

In terms of managerial implications, firms that do not work with relationship banks and depend primarily on soft information can develop the relationships with trade creditors to access credit.

## References

- Agostino, M., Trivieri, F. (2014). Does trade credit play a signalling role? Some evidence from SMEs microdata. *Small Business Economics* 42(1), 131-151.
- Aiello, F., Bonanno, G. (2015). Looking at the determinants of efficiency in banking: Evidence from Italian mutual-cooperatives. *International Review of Applied Economics* 30 (4), 507-526.
- Alessandrini, P., Presbitero, A., Zazzaro, A. (2010). Bank size or distance: What hampers innovation adoption by SMEs? *Journal of Economic Geography* 10, 845-881.
- Andrieu, G., Stagliano, R., Van Der Zwan, P. (2018). Bank debt and trade credit for SMEs in Europe: firm-, industry-, and country-level determinants. *Small Business Economics* 51, 245-264.
- Atanasova, C. (2012). How do firms choose between intermediary and supplier finance? *Financial Management* 41 (1), 207-228.
- Bartoli, F., Ferri, G., Murro, P., Rotondi, Z. (2011). Soft information and loan supply crisis. Evidence from the credit files of a large bank. *Rivista Bancaria-Minerva Bancaria* 5, 7-28.
- Bartoli, F., Ferri, G., Murro, P., Rotondi, Z. (2013). SME financing and the choice of lending technology in Italy: Complementarity or substitutability? *Journal of Banking and Finance* 37, 5476-5485.
- Berger, A., Black, L. (2011). Bank size, lending technologies, and small business finance. *Journal of Banking and Finance* 35 (3), 724-735.
- Berger, A., Miller, N., Petersen, M., Rajan, R., Stein, J. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76, 237-269.
- Berger, A., Udell, G. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business* 68, 351-382.
- Berger, A. N., Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal* 112 (477), F32-F53.
- Berger, A., Udell, G. (2006). A more complete conceptual framework for SME financing. *Journal of Banking and Finance* 30, 2945-2966.
- Biais, B., Gollier, C. (1997). Trade credit and credit rationing. *Review of Financial Studies* 10, 903-937.
- Bianco, M., Jappelli, T., Pagano, M. (2005). Courts and banks: Effects of judicial enforcement on credit markets. *Journal of Money, Credit and Banking* 37, 223-245.
- Bonaccorsi Di Patti, E., Gobbi, G. (2007). Winners or losers? The effects of banking consolidation on corporate borrowers. *Journal of Finance* 62, 669-695.
- Brennan, M., Maksimovic, V., Zechner, J. (1988). Vendor financing. *Journal of Finance* 43, 1127-1141

- Burkart, M., Ellingsen, T. (2004). In-kind finance: A theory of trade credit. *American Economic Review* 94 (3), 569-590
- Caprio, G., Laeven, L., Levine, R. (2007). Governance and bank valuation, *Journal of Financial Intermediation*, 16 (4), 584-617
- Casey, E., O'Toole, C. (2014). Bank lending constraints, trade credit and alternative financing during the financial crisis: Evidence from European SMEs. *Journal of Corporate Finance* 27, 173-193.
- Cosci, S., Guida, R., Meliciani, V. (2020). Does trade credit really help relieving financial constraints? *European Financial Management* 26, 198-215.
- Cucculelli, M., Peruzzi, V., Zazzaro, A. (2019). Relational capital in lending relationships: Evidence from European family firms. *Small Business Economics* 52, 277-301.
- Cuñat, V. (2007). Trade credit: Suppliers as debt collectors and insurance providers. *Review of Financial Studies* 20, 491-527.
- Dass, N., Kale, J. R., Nanda, V. (2015). Trade credit, relationship-specific investment, and product market power. *Review of Finance* 19, 1867-1923.
- De Bodt, E., Lobež, F., Statnik, J.C. (2015). Crise bancaire et PME: la double peine. *Working Paper*.
- Demirgüç-Kunt, A., Maksimovic, V. (2002). Firms as financial intermediaries – evidence from trade credit data. *Policy Research Working Paper Series*. The World Bank.
- D'Onofrio, A., Minetti, R., Murro, P. (2019). Banking development, socio-economic structure and income inequality. *Journal of Economic Behavior & Organization* 157, 428-451.
- Fabbri, D., Klapper, L. F. (2016). Bargaining power and trade credit. *Journal of Corporate Finance* 41, 66-80.
- Fabbri, D., Menichini, A.M. (2010). Trade credit, collateral liquidation, and borrowing constraints. *Journal of Financial Economics* 96, 413-432.
- Ferri, G., Murro, P. (2015). Do firm–bank ‘odd couples’ exacerbate credit rationing? *Journal of Financial Intermediation* 24, 231-251.
- Ferri, G., Murro, P., Peruzzi, V., Rotondi, Z. (2019). Bank lending technologies and credit availability in Europe: What can we learn from the crisis? *Journal of International Money and Finance* 95, 128-148.
- Ferris, J.S. (1981). A transaction theory of trade credit use. *Quarterly Journal of Economics* 94, 243-270.
- Garcia-Appendini, E., Montoriol-Garriga, J. (2013). Firms as liquidity providers: Evidence from the 2007-2008 financial crisis. *Journal of Financial Economics* 109, 272-291.
- Giannetti, M., (2003). Do better institutions mitigate agency problems? Evidence from corporate finance choices. *Journal of Financial and Quantitative Analysis* 38, 185-212.



- Giannetti, M., Burkart, M., Ellingsen, T. (2011). What you sell is what you lend? Explaining trade credit contracts. *The Review of Financial Studies* 24, 1261-1298.
- Guiso, L. Sapienza, P., Zingales, L. (2004). The role of social capital in financial development. *American Economic Review* 94, 526-556
- Hale, G., (2012). Bank relationships, business cycles, and financial crises. *Journal of International Economics*, 88, 312-325. .
- Herrera, M., Minetti, R. (2007). Informed finance and technological change: Evidence from credit relationships. *Journal of Financial Economics* 83, 223-269.
- Hertzberg, A., Liberti, J., Paravisini, D. (2010). Information and incentives inside the firm: Evidence from loan officer rotation. *The Journal of Finance* 65(3), 795-828.
- Huyghebaert, N. (2006). On the determinants and dynamics of trade credit use: Empirical evidence from business start-ups. *Journal of Business Finance and Accounting* 33 (1-2), 305-328.
- Hyun, J. (2021). Trade credit, group affiliation, and credit contraction: Evidence from the 1997 Korean financial crisis, *Economic Modelling* 95, 203-214.
- Johnson, S., McMillan, J., Woodruff, C., 2002. Courts and relational contracts. *Journal of Law, Economics, and Organization* 18 (1), 221-277.
- Klapper, L., Laeven, L., Rajan, R. (2012). Trade credit contracts. *Review of Financial Studies* 25 (3), 838-867.
- Liberti, J., Mian, A. R. (2009). Estimating the effect of hierarchies on information use. *Review of Financial Studies* 22(10), 4057-4090.
- Mateut, S., Bougheas, S., Mizen, P. (2006). Trade credit, bank lending and monetary policy transmission. *European Economic Review* 50, 603-629.
- McMillan, J., Woodruff, C. (1999). Interfirm relationship and informal credit in Vietnam. *The Quarterly Journal of Economics* 114, 1285-1320.
- McNamara, A., Murro, P., O' Donohoe, S. (2017). Countries lending infrastructure and capital structure determination: The case of European SMEs. *Journal of Corporate Finance* 43, 122-138.
- Mian, S. L., Smith J. C. W. (1992). Accounts receivable management policy: theory and evidence. *The Journal of Finance* 47 (1), 169-200.
- Minetti, R. (2011). Informed finance and technological conservatism. *Review of Finance* 15 (3), 633-692.
- Minetti, R., Murro, P., Rotondi, Z., Zhu, S. C. (2019). Financial constraints, firms' supply chains, and internationalization. *Journal of the European Economic Association*, 17 (2), 327-375.
- Minetti, R., Zhu, S. (2011). Credit constraints and firm export: Microeconomic evidence from Italy. *Journal of International Economics*, 83 (2), 109-125.

- Molina, C. A., Preve, L. A. (2012). An empirical analysis of the effect of financial distress on trade credit. *Financial Management* 41 (1), 187-205.
- Murro, P. (2013). The determinants of innovation: What is the role of risk? *The Manchester School* 81 (3), 293-323.
- Murro, P., Peruzzi, V. (2019). Family firms and access to credit. Is family ownership beneficial? *Journal of Banking & Finance* 101, 173-187.
- Murro, P., Peruzzi, V. (2021). Relationship lending and the use of trade credit: the role of relational capital and private information. *Small Business Economics*, forthcoming.
- Ng, C. K., Smith, J. K., Smith, R. L. (1999). Evidence on the determinants of credit terms used in interfirm trade. *The Journal of Finance* 54, 110-1129
- Niskanen, J., Niskanen, M. (2006). The determinants of corporate trade credit policies in a bank-dominated financial environment: The case of Finnish small firms. *European Financial Management* 12 (1), 81-102.
- Palacin-Sánchez, M. J., Canto-Cuevas, F. J., di Pietro, F. (2019). Trade credit versus bank credit: a simultaneous analysis in European SMEs. *Small Business Economics* 53 (4), 1079-1096.
- Petersen, M., Rajan, R. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance* 49, 3-37.
- Presbitero, A. F., Zazzaro, A. (2011). Competition and relationship lending: Friends or foes?. *Journal of Financial Intermediation* 20 (3), 387-413.
- Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance* 47 (4), 1367-1400.
- Sharpe, S. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The Journal of Finance* 45, 1069-1087.
- Smith, J. K. (1987). Trade credit and information asymmetry. *The Journal of Finance* 42, 863-872.
- Stein, J. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance* 57, 1891-1921.
- Uchida, H., Udell, G., Watanabe, W. (2013). Are trade creditors relationship lenders? *Japan and the World Economy* 25-26, 24-38.
- Uchida, H., Udell, G., Yamori, N. (2012). Loan officers and relationship lending to SMEs. *Journal of Financial Intermediation* 21, 97-112.
- Wilner, B. (2000). The exploitation of relationships in financial distress: The case of trade credit. *The Journal of Finance* 55, 153-178.

**Table A1. Variable descriptions and sources**

<b>Variable</b>	<b>Description</b>
<i>Dependent variables</i>	
TC/TL	Ratio of firm's trade credit to total loans as of the end of December 2006
TC/TA	Ratio of firm's trade credit to total assets as of the end of December 2006
TC/STL	Ratio of firm's trade credit to total short-term loans as of the end of December 2006
DPO	Days payable outstanding (average trade payable/cost of goods sold) * 360
<i>Variables of interest</i>	
SOFT	We use a question from the survey: "Which characteristics are key in selecting your main bank?" Respondents assigned a value (from 1–4), in descending order of importance, to two characteristics (among others): "The bank knows you and your business" and "You have frequent contacts with the credit officer at the bank." The soft dummy variable takes a value of 1 if the firm chooses the highest value for both these two characteristics (Bartoli et al., 2013).
LT_TRANS	Global index for transactional lending technology; we use a question in the survey: "In your view, which criteria does your bank follow in granting loans to you?" Respondents assigned weights, from 1 (very much) to 4 (nil), to 15 factors. LT_TRANS is an average of six dummy variables that take a value of 1 if the firm answered "1" to lending factors 1, 2, 3, 4, 5, 6, and 8 (Bartoli et al., 2013).
LT_FS	Index for financial statement technology; LT_FS is an average of four dummy variables that take a value of 1 if the firm answered "1" to lending factors 1, 2, 3, and 4 (same question as LT_TRANS).
LT_RE	Index for real estate technology; LT_RE is a dummy equal to 1 if the firm answers "1" to lending factor 5 (same question as LT_TRANS).
LT_OF	Index for other fixed-asset technology; LT_OF is an average of four dummy variables that take a value of 1 if the firm answered "1" to lending factors 6 and 8 (same question as LT_TRANS).
LT_REL	Index for relationship lending technology; we use a question in the survey: "In your view, which criteria does your bank follow in granting loans to you?" Respondents assigned weights from 1 (very much) to 4 (nil) to 15 factors. LT_REL is an average of six dummy variables that take a value of 1 if the firm answered "1" to lending factors 9, 10, 11, 13, 14, and 15 (Bartoli et al., 2013).
MAINTRANS	1 if LT_TRANS is larger than the 75% percentile of the distribution and LT_REL is lower than 75%
MAINREL	1 if LT_REL is larger than the 75% percentile of the distribution and LT_TRANS is lower than 75%
<i>Control variables</i>	
<i>Firm variables</i>	
LEVERAGE	Ratio of firm's total loans to its total assets as of the end of December 2006/1,000
Firm Age	Log(1 + firm age)
PROFIT	Log(1+ Profit of the firm as the end of December 2006)
FA/TA	Ratio of firm's fixed assets to total assets as the end of December 2006
Firm Size	Log(1 + firm number of employees)
CORPORATION	1 if the firm is a corporation

GROUP	1 if the firm belongs to a group
CONSORTIUM	1 if the firm is a member of a consortium
AUDIT	1 if the firm has a certified accounting statement
Credit Rationed	Dummy that takes a value of 1 if the firm answers “yes” to the question “In 2006, would your firm have wished a larger amount of loans at the prevailing interest rate agreed with the bank?” and to at least one of the following two questions: “In 2006, did the firm demand more credit than it actually obtained?” or “To obtain more credit, were you willing to pay a higher interest rate?” (Survey of Italian Manufacturing Firms)
Rel. Length	$\text{Log}(1 + \text{length of the relationship between the firm and the bank})$
Log(Bank)	$\text{Log}(1 + \text{number of banks the firm deals with})$
Province	Set of dummies for each Italian province (in Italy, there are 110 provinces)
Sector	Set of dummies equal to 1 if the firm belongs to one of six sectors: agriculture, wholesale, construction, industrial production, service, transport
<i>Bank variables</i>	
NATIONAL BANK	1 if the main bank is either a national or a foreign bank; 0 if the main bank is a smaller-sized cooperation mutual bank, a larger-sized cooperative bank, a saving bank, or other types of bank
<i>Macroeconomic variables</i>	
GDP	Log of the value of the GDP in the province as of the end of December 2006
HHI	Hirschman-Herfindahl index calculated using the number of branches per bank in every province
Loans/Deposit	The ratio of deposits to loans at the provincial level
Social Capital	Voter turnout at the province level for all the referenda before 1989 (Guiso et al., 2004)
Civil suits	The average number of civil suits pending in the judicial district in 1998–2000, per 1,000 inhabitants (Herrera and Minetti, 2007)
<i>Instrumental variables</i>	
Province LT_TRANS	The average value of transactional lending technology for the firms in the province
Province LT_REL	The average value of relationship lending technology for the firms in the province
L.O. Turnover	1 if the loan officer of the firm’s main bank changes during the 2001–2006 period
Banks’ M&A	The total number of mergers and acquisitions in the province during 2002–2006 (SBB1)
Functional distance	Average banks’ functional distance between hierarchical levels in the province during the period 2000–2005 (Alessandrini et al., 2010)
Self-Confident	Average of the dummies constructed on the characteristics 7, 8, 9, 10, 11, 12, and 14 from the question in Table 2

**Table A2. Sample summary statistics**

	<b>Full Sample</b>		<b>Analysis Sample</b>		<b>t-test</b>
	<b>Mean</b>	<b>Std. Dev.</b>	<b>Mean</b>	<b>Std. Dev.</b>	
<i>Firm characteristics</i>					
TC/TL	0.273	0.235	0.203	0.199	0.070
TC/TA	0.627	0.587	0.433	0.453	0.194
TC/STL	0.325	0.33	0.227	0.247	0.098
DPO	104.858	112.706	86.088	92.825	18.770
Number of Bank	4.985	3.901	5.592	4.271	-0.607
Rel. Length	2.688	0.705	2.717	0.676	-0.029
Firm Age	28.783	23.922	30.247	23.063	-1,464*
Profit	8.794	1.518	8.967	1.908	-0.173
FA/TA	0.266	0.178	0.279	0.183	-0.013
Firm Size (number of employees)	87.686	314.701	138.405	474.925	-50.719*
LEVERAGE	0.006	0.359	0.025	0.777	-0.019
CORPORATION	0.949	0.219	0.967	0.176	-0.018
GROUP	0.188	0.391	0.256	0.437	-0.068
CONSORTIUM	0.032	0.177	0.033	0.179	-0.001
Sectors:					
- Agriculture	0.001	0.030	0.001	0.032	0.000
- Wholesale	0.054	0.211	0.056	0.230	-0.002
- Construction	0.053	0.231	0.058	0.234	-0.005
- Industrial Production	0.879	0.338	0.878	0.327	0.001
- Service	0.009	0.079	0.005	0.072	0.004
- Transport	0.004	0.032	0.002	0.032	0.002
<i>Financial information</i>					
SOFT			0.087	0.282	
LT_TRANS			0.130	0.241	
LT_REL			0.123	0.258	
Credit Rationed			0.062	0.241	
AUDIT			0.244	0.429	
NATIONAL BANK			0.353	0.478	
<i>Macroeconomic variables</i>					
GDP	10.220	0.188	10.221	0.182	
HHI	0.097	0.036	0.099	0.037	
Loans / Deposit	1.943	0.586	1.915	0.569	
Civil Suits	0.003	0.005	0.003	0.005	
Social Capital	0.846	0.054	0.847	0.055	
<i>Instrumental variables</i>					
Province LT_TRANS			0.131	0.081	
Province LT_REL			0.123	0.089	
L.O. Turnover			0.267	0.443	
Banks' M&A			0.251	0.301	
Functional distance			2.873	0.825	
Self-Confident			0.147	0.272	
<b>Observations</b>	4,504		962		

**Table A3. Correlation matrix**

The table provides the pairwise correlation matrix. The numbers in brackets indicate the  $p$ -value of the test of significance: \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ .

	TC/TL	TC/TA	TC/STL	DPO	SOFT	LT_REL	LT_TRANS
TC/TL	1.0000 [0.0000]						
TC/TA	0.9344*** [0.0000]	1.0000 [0.0000]					
TC/STL	0.9451*** [0.0000]	0.8810*** [0.0000]	1.0000 [0.0000]				
DPO	0.7994*** [0.0000]	0.7945*** [0.0000]	0.7693*** [0.0000]	1.0000 [0.0000]			
SOFT	0.0214 [0.5051]	0.0110 [0.7313]	0.0133 [0.6805]	0.0811** [0.0116]	1.0000 [0.0000]		
LT_REL	0.0346 [0.2814]	0.0335 [0.2964]	0.0394 [0.2209]	0.0579* [0.0720]	0.2062*** [0.0000]	1.0000 [0.0000]	
LT_TRANS	0.0379 [0.2379]	0.0384 [0.2317]	0.0480 [0.1364]	0.0512 [0.1117]	0.1922*** [0.0000]	0.6404*** [0.0000]	1.0000 [0.0000]

**Table A4. Determinants of the proportion of trade credit to total loan**

The regressions show the impact of using soft information and lending technologies, divided into four indicators, on the quantity of trade credit as a proportion of the total loan. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

	(1)	(2)	(3)	(4)	(5)
	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	−0.052 [0.105]	−0.060* [0.097]	−0.024 [0.460]	−0.033 [0.303]	−0.052 [0.140]
LT_REL	0.014 [0.765]	0.043 [0.304]	−0.001 [0.981]	0.007 [0.872]	0.027 [0.567]
SOFT * LT_REL	−0.240* [0.072]	−0.085 [0.394]	−0.115 [0.257]	−0.041 [0.698]	−0.252* [0.063]
LT_TRANS	−0.003 [0.947]				
SOFT * LT_TRANS	0.390*** [0.005]				
LT_FS		−0.035 [0.280]			−0.047 [0.166]
SOFT * LT_FS		0.181* [0.052]			0.185** [0.042]
LT_RE			0.019 [0.528]		0.030 [0.357]
SOFT * LT_RE			0.207** [0.014]		0.175* [0.061]
LT_OF				0.010 [0.839]	0.008 [0.871]
SOFT * LT_OF				0.129 [0.215]	0.021 [0.846]
Credit Rationed	−0.001 [0.966]	−0.006 [0.834]	0.001 [0.962]	0.000 [0.998]	−0.003 [0.923]
AUDIT	0.004 [0.807]	0.006 [0.698]	0.004 [0.827]	0.004 [0.812]	0.005 [0.763]
Log(bank)	−0.028* [0.087]	−0.028* [0.097]	−0.030* [0.070]	−0.027 [0.103]	−0.030* [0.067]
Rel. Length	−0.003 [0.776]	−0.006 [0.614]	−0.002 [0.859]	−0.003 [0.775]	−0.004 [0.728]
Firm Age	0.037***	0.037***	0.036***	0.036***	0.037***



PROFIT	[0.001] 0.002 [0.740]	[0.001] 0.002 [0.717]	[0.001] 0.001 [0.801]	[0.001] 0.002 [0.711]	[0.001] 0.001 [0.789]
FA/TA	0.038 [0.300]	0.039 [0.286]	0.034 [0.360]	0.040 [0.281]	0.033 [0.372]
Firm Size	-0.002 [0.810]	-0.003 [0.747]	-0.001 [0.893]	-0.003 [0.720]	-0.001 [0.889]
LEVERAGE	-0.011*** [0.000]	-0.011*** [0.000]	-0.011*** [0.000]	-0.011*** [0.000]	-0.011*** [0.000]
CORPORATION	0.056 [0.124]	0.052 [0.157]	0.059 [0.109]	0.050 [0.166]	0.061* [0.098]
GROUP	-0.020 [0.264]	-0.019 [0.291]	-0.022 [0.229]	-0.020 [0.284]	-0.020 [0.281]
CONSORTIUM	-0.031 [0.412]	-0.027 [0.478]	-0.036 [0.334]	-0.026 [0.509]	-0.034 [0.363]
NATIONAL BANK	0.016 [0.313]	0.015 [0.348]	0.016 [0.291]	0.015 [0.356]	0.017 [0.273]
GDP	0.956** [0.017]	0.933** [0.020]	0.975** [0.015]	0.945** [0.017]	0.976** [0.017]
HHI	16.971*** [0.002]	16.907*** [0.002]	17.267*** [0.001]	16.437*** [0.002]	17.819*** [0.001]
Loans/Deposit	0.556*** [0.000]	0.563*** [0.000]	0.567*** [0.000]	0.542*** [0.000]	0.587*** [0.000]
Civil Suits	82.221*** [0.000]	83.166*** [0.000]	83.569*** [0.000]	84.781*** [0.000]	82.517*** [0.000]
Province Indicators	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes
Constant	-12.885*** [0.005]	-12.638*** [0.006]	-13.125*** [0.004]	-12.695*** [0.005]	-13.221*** [0.004]
Observations	962	962	962	962	962
R <sup>2</sup>	0.145	0.140	0.144	0.138	0.148
Adjusted R <sup>2</sup>	0.027	0.022	0.026	0.020	0.027

**Table A5. Robustness tests**

These regressions show the impact of using soft information and lending technologies on the use of trade credit (measured by three proxies). We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	TC/TA	TC/STL	DPO	TC/TL	TC/TA	TC/STL	DPO
SOFT	−0.058 [0.174]	−0.102 [0.158]	−8.383 [0.609]	−0.039 [0.173]	−0.043 [0.249]	−0.080 [0.208]	6.873 [0.666]
LT_REL	−0.000 [0.999]	0.033 [0.751]	4.451 [0.812]				
SOFT * LT_REL	−0.187 [0.310]	−0.457 [0.144]	−63.782 [0.336]				
LT_TRANS	0.008 [0.887]	0.040 [0.723]	−4.725 [0.811]				
SOFT * LT_TRANS	0.328* [0.088]	0.699** [0.031]	156.501** [0.027]				
MAINREL				−0.048 [0.251]	−0.069 [0.160]	−0.076 [0.406]	−24.785 [0.137]
SOFT * MAINREL				−0.134** [0.041]	−0.174** [0.045]	−0.376** [0.012]	−81.184*** [0.005]
MAINTRANS				−0.028 [0.224]	−0.032 [0.262]	−0.053 [0.326]	−13.777 [0.151]
SOFT * MAINTRANS				0.154*** [0.008]	0.146* [0.060]	0.302** [0.021]	64.366** [0.036]
Control Variables	All	All	All	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−15.106** [0.016]	−26.411*** [0.007]	−4.7e + 03*** [0.005]	−13.494*** [0.004]	−15.659** [0.013]	−27.868*** [0.005]	−5.0e + 03*** [0.003]
Observations	962	962	962	962	962	962	962
R <sup>2</sup>	0.129	0.147	0.166	0.145	0.132	0.148	0.168
Adjusted R <sup>2</sup>	0.009	0.030	0.052	0.028	0.013	0.031	0.054

**Table A6. Firm characteristics**

These regressions show the impact of using soft information and lending technologies on the quantity of trade credit as a proportion of the total loan, splitting the sample according to some firm characteristics. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

	By number of employees		By firm age (year)		By audited	
	≤ mean	> mean	≤ mean	> mean	Not audited	Audited
	(1)	(2)	(3)	(4)	(5)	(6)
	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	0.006 [0.910]	-0.093** [0.032]	0.080 [0.277]	-0.116*** [0.001]	-0.031 [0.397]	-0.296*** [0.000]
LT_REL	0.036 [0.649]	0.004 [0.947]	-0.019 [0.780]	0.006 [0.922]	-0.020 [0.697]	0.169 [0.335]
SOFT * LT_REL	0.086 [0.646]	-0.327*** [0.005]	0.103 [0.576]	-0.352*** [0.001]	-0.167 [0.326]	-0.194 [0.423]
LT_TRANS	0.074 [0.316]	-0.071 [0.302]	0.092 [0.225]	-0.036 [0.572]	0.041 [0.457]	-0.085 [0.429]
SOFT * LT_TRANS	-0.059 [0.775]	0.604*** [0.000]	-0.181 [0.392]	0.679*** [0.000]	0.255 [0.148]	0.743*** [0.001]
Control Variables	All	All	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.908 [0.822]	-68.303* [0.069]	-1.579 [0.924]	-15.373** [0.013]	-14.812*** [0.003]	-30.017 [0.370]
Observations	470	492	419	543	727	235
R <sup>2</sup>	0.247	0.251	0.226	0.259	0.165	0.391
Adjusted R <sup>2</sup>	0.027	0.057	-0.008	0.084	0.018	-0.011

**Table A7. Firm–bank relationship**

These regressions show the impact of using soft information and lending technologies on the quantity of trade credit as a proportion of the total loan, splitting the sample according to some characteristics of the firm–bank relationship. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

	By number of banks		By length of relationship	
	≤ 3 banks	> 3 banks	≤ 2 years	> 2 years
	(1)	(2)	(3)	(4)
	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	−0.075 [0.256]	−0.047 [0.254]	−0.107 [0.112]	−0.019 [0.630]
LT_REL	0.050 [0.552]	0.023 [0.701]	0.054 [0.625]	−0.011 [0.841]
SOFT * LT_REL	−0.306 [0.176]	−0.184 [0.329]	−0.127 [0.561]	−0.208 [0.182]
LT_TRANS	−0.075 [0.334]	0.002 [0.971]	−0.010 [0.934]	−0.003 [0.956]
SOFT * LT_TRANS	0.537** [0.026]	0.321 [0.112]	0.260 [0.342]	0.369** [0.026]
Control Variables	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes
Constant	2.024 [0.928]	−11.306** [0.032]	−33.736 [0.157]	−12.365** [0.010]
Observations	350	612	244	718
R <sup>2</sup>	0.322	0.198	0.341	0.168
Adjusted R <sup>2</sup>	0.072	0.029	−0.040	0.016

**Table A8. Bank characteristics**

These regressions show the impact of the use of soft information and lending technologies on the quantity of trade credit as a proportion of the total loan, splitting the sample according to some characteristics of the main bank identified by the firm. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

	By bank type		By turnover	
	National	Local	No turnover	Turnover
	(1)	(2)	(3)	(4)
	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	-0.050 [0.294]	-0.054 [0.291]	-0.047 [0.223]	-0.027 [0.729]
LT_REL	-0.067 [0.374]	0.038 [0.604]	0.022 [0.690]	-0.051 [0.624]
SOFT * LT_REL	-0.150 [0.462]	-0.222 [0.183]	-0.244 [0.164]	-0.376 [0.119]
LT_TRANS	0.079 [0.355]	-0.047 [0.462]	0.009 [0.883]	0.028 [0.775]
SOFT * LT_TRANS	0.274 [0.208]	0.440** [0.010]	0.351* [0.052]	0.531* [0.058]
Control Variables	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes
Constant	-9.175 [0.193]	-10.397 [0.524]	-13.806** [0.014]	23.788 [0.628]
Observations	340	622	705	257
R <sup>2</sup>	0.331	0.160	0.190	0.281
Adjusted R <sup>2</sup>	0.066	-0.012	0.040	-0.076

**Table A9. Economic environment**

These regressions show the impact of the use of soft information and lending technologies on the quantity of trade credit as a proportion of the total loan, splitting the sample according to the socioeconomic conditions of the province in which the firm is located. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

	By area			By social capital	
	North	Center	South	≤ mean	> mean
	(1)	(2)	(3)	(4)	(5)
	TC/TL	TC/TL	TC/TL	TC/TL	TC/TL
SOFT	−0.067*	0.002	0.121	−0.077	−0.050
	[0.065]	[0.985]	[0.396]	[0.244]	[0.183]
LT_REL	−0.028	0.145	0.058	−0.069	0.044
	[0.588]	[0.218]	[0.699]	[0.425]	[0.398]
SOFT * LT_REL	−0.189	−0.748**	−0.343	0.052	−0.388***
	[0.206]	[0.019]	[0.577]	[0.850]	[0.000]
LT_TRANS	0.025	−0.109	−0.091	−0.010	−0.003
	[0.630]	[0.418]	[0.571]	[0.905]	[0.959]
SOFT * LT_TRANS	0.371**	0.547*	0.018	0.143	0.521***
	[0.021]	[0.058]	[0.977]	[0.632]	[0.000]
Control Variables	All	All	All	All	All
Province Indicators	Yes	Yes	Yes	Yes	Yes
Sector Indicators	Yes	Yes	Yes	Yes	Yes
Constant	−109.704***	40.485	11.057***	18.560	−63.826**
	[0.000]	[0.811]	[0.003]	[0.760]	[0.011]
Observations	688	166	108	287	675
R <sup>2</sup>	0.116	0.260	0.552	0.275	0.116
Adjusted R <sup>2</sup>	0.024	0.023	0.160	0.044	0.018

**Table A10. Instrumental variable regression**

These regressions show the impact of the use of soft information and lending technologies on the quantity of trade credit as a proportion of the total loan, using an instrumental variable approach. We control for bank–firm relationship and firm characteristic variables. See Table A1 and Section 3 for details on the variables. The regression is robust to heteroskedasticity. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$  (as indicated in brackets).

<b>First stage IV regression</b>				
	(1)	(2)	(3)	
	LT_TRANS	LT_REL	SOFT	
<i>Instrumental variables</i>				
Province LT_TRANS	0.326 [0.699]	-1.644 [0.319]		
Province LT_REL	-0.099 [0.881]	1.619 [0.244]		
L.O. Turnover	0.033** [0.018]	-0.035** [0.011]		
Banks' M&A	-0.401 [0.200]	0.182 [0.677]		
Functional distance	0.004 [0.932]	-0.142* [0.078]		
Self-Confident			-0.234*** [0.000]	
Control	All	All	All	
Observations	962	962	962	
F-test Weak Instrument	17.56	23.51	13.41	
R <sup>2</sup>	0.642	0.648	0.203	
Adjusted R <sup>2</sup>	0.593	0.600	0.095	
<b>Second stage IV regression</b>				
	(1)	(2)	(3)	(4)
	TC/TL	TC/TA	TC/STL	DPO
SOFT*	-0.075 [0.663]	-0.043 [0.848]	-0.392 [0.319]	-40.424 [0.586]
LT_REL*	-0.096 [0.261]	-0.106 [0.304]	-0.161 [0.413]	-61.188* [0.081]
SOFT* # LT_REL*	-1.122** [0.017]	-1.156* [0.067]	-2.394** [0.036]	-525.707** [0.019]
LT_TRANS*	0.168* [0.084]	0.152 [0.196]	0.409* [0.066]	78.504* [0.056]
SOFT* # LT_TRANS*	1.089** [0.011]	1.168** [0.043]	2.364** [0.022]	614.799*** [0.003]
Control	All	All	All	All
Observations	962	962	962	962
R <sup>2</sup>	0.142	0.128	0.148	0.165
Adjusted R <sup>2</sup>	0.024	0.009	0.031	0.052